Science of the Total Environment 755 (2021) 143338

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Estimating greenhouse gas emissions from direct land use change due to crop production in multiple countries

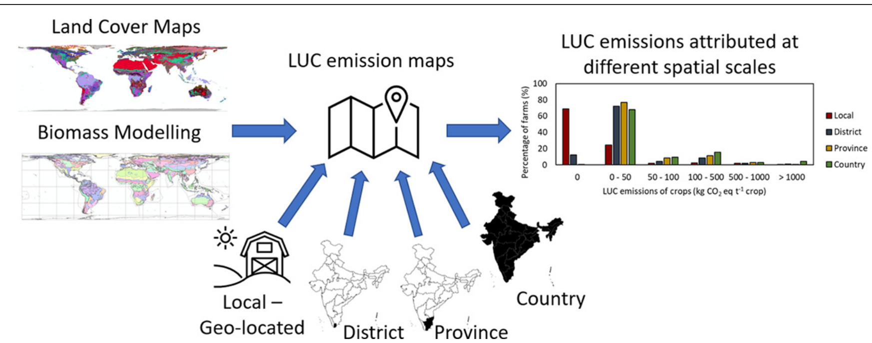
Wan Yee Lam [a,*], Julia Chatterton [b], Sarah Sim [b], Michal Kulak [b], Angelica Mendoza Beltran [b], Mark A.J. Huijbregts [a]

[a] *Department of Environmental Science, Institute for Water and Wetland Research, Radboud University, P.O. Box 9010, 6500, GL, Nijmegen, the Netherlands*
[b] *Unilever Safety and Environmental Assurance Centre, Unilever R&D, Colworth Science Park, Sharnbrook, Bedfordshire MK44 1LQ, United Kingdom*

HIGHLIGHTS

- LUC of crops estimated with national statistics neglects intra-country variability.
- Approximate farm locations were used to estimate LUC emissions of 1885 farms.
- 33% of farms were identified to have LUC emissions at the local scale.
- Analysis at coarser spatial scales typically overestimated LUC emissions of crops.
- Local level farm location needs to be collected to better represent LUC dynamics.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 22 August 2020
Received in revised form 20 October 2020
Accepted 21 October 2020
Available online 29 October 2020

Editor: Damia Barcelo

Keywords:
Agricultural life cycle assessment
Spatial assessment
Life cycle greenhouse gas footprinting
Land cover change

ABSTRACT

Greenhouse gas (GHG) emissions from direct land use change (LUC) in GHG footprint studies of crops are often estimated using national land use change statistics, as in many cases the exact location of crop cultivation and land use history is unknown. As such, these studies neglect spatial variability in land use change (amount and configuration) at the sub-national level as well as spatial variability in natural carbon stocks. For this reason, a spatial approach that enables consistent implementation of LUC emissions of crop production at different locations is developed and applied in this study. The dataset of crop production covers 69 crops cultivated on 1885 farms in 33 countries, spanning North and South America, Asia, Australia and Oceania, Europe and Africa, in the year 2014. Of the 1885 farms, 33% (619 farms) were identified to have LUC emissions when estimated at the local scale. LUC emissions of farms, derived using local scale location information, were found to have little correlation with those estimated at coarser spatial scales (such as the province or country level) using the spatial approach in this study or estimated using accounting approaches based on national statistics. Analysis at coarser spatial scales typically overestimated the LUC emissions of crops, as LUC in other regions can heavily influence these estimates. Therefore, it is concluded that local scale LUC emissions better represent local LUC dynamics, thereby improving the reliability of GHG footprint studies.

1. Introduction

Land use change (LUC) from agricultural expansion is a major source of anthropogenic greenhouse gas (GHG) emissions (Houghton et al., 2012), with agriculture, forestry and other land use (AFOLU) contributing about 23% of the global anthropogenic GHG emissions in 2007–2016

* Corresponding author at: P.O. Box 9010 (mailbox no 89), NL-6500, GL, Nijmegen, the Netherlands.
E-mail address: lamwanyee@science.ru.nl (W.Y. Lam).

https://doi.org/10.1016/j.scitotenv.2020.143338

(IPCC, 2019). Moreover, variability of emissions from deforestation and from cultivated organic soils drive, on average, 42% of the variance in product agricultural GHG emissions, according to the meta-analysis conducted by Poore and Nemecek (2018). To support climate and land use policies, methods exist to attribute GHG emissions from LUC (or LUC emissions) to particular products or activities (BSI, 2012; Davis et al., 2014; Flynn et al., 2012). Davis et al. (2014) reviewed a range of these methods and recommended attribution of LUC emissions to agricultural products using spatially-explicit data. To do this, information about the location of LUC, the previous land cover and related carbon stocks of previous and current land cover are needed. Lam et al. (2019) applied a spatial approach to attribute LUC emissions to crude palm oil in Indonesia. However, such an exercise has not been performed at the global scale nor for a large range of crops. This is because transparency of crop production locations is often limited in global supply chains and global land use and land cover (LULC) maps at high spatial resolution and with temporal coverage over decades, have not been available for GHG footprint calculations (Kulak et al., 2018; van Beijma et al., 2018). LUC emissions in GHG footprint studies of crops and bio-based products (Peter et al., 2017; Wang et al., 2018) are hence often neglected or estimated using national statistics of crop production and land changes and with continental average carbon stock values of agro-ecological zones, following PAS2050-1 methodology (BSI, 2012). However, average estimates of LUC emissions for various crop-country combinations may result in large uncertainties and thus may be of limited relevance for informing GHG mitigation and sourcing initiatives within specific supply chains, or spatially explicit verification of compliance with corporate zero-deforestation commitments (Lambin et al., 2018). This mismatch between the LUC emission estimates from local information and those derived from data with lower spatial resolution, i.e. province and country scale, is well documented in previous studies (Powers et al., 2011).

The implementation of sustainable agriculture programs by companies has led to enhanced transparency of crop production locations as well as farm-level data, e.g. yields required for calculating GHG footprints of crops (Smith et al., 2019; Unilever, 2018). Furthermore, a global spatially-resolved LULC dataset for the period 1992 to 2015 has become available (ESA, 2017). Together with forest biomass maps at pan-tropical (Avitabile et al., 2016; Baccini et al., 2012; Saatchi et al., 2011) and global scale (Santoro, 2018), the LULC dataset may be suitable to estimate spatially explicit carbon stock changes due to cropland expansion over time.

Here, a new spatial approach to estimate GHG emissions from direct LUC due to crop production is developed and demonstrated. This enabled calculation of LUC emissions due to cropland expansion in the 20-year period at 300 m × 300 m resolution which could then be, attributed to farm-specific crop production using approximate production locations, e.g. nearest town, district, province or country, as well as farm-specific crop yields. To demonstrate the approach, crop production dataset covering 69 crops cultivated on 1885 farms in 2014 in 33 countries was used to explore the relevance of location specificity, LUC emission estimates from spatial versus statistical approaches and the relative importance of LUC emissions for crop GHG footprints. (See S7 of Supplementary Information (SI); data were obtained from within the supply base compliant with Unilever's Sustainable Agriculture Code (Smith et al., 2015)). These three aspects are considered in more detail next.

First, using the spatial approach outlined above, the importance of the level of spatial approximation of farm locations was tested by comparing local scale LUC emissions (derived from information on the nearest town) with those estimated at coarser spatial scales (district, province and country). This comparison was undertaken because many people and organisations interested in calculating crop-specific LUC emissions for crop GHG footprinting purposes may have limited access to farm location data. They may often rely on coarse location to derive emissions estimates. Secondly, the emissions estimated using the spatial approach above, were compared with those estimated using the PAS2050-1 methodology to illustrate the uncertainty of LUC emission estimates from the different methods. In particular, LUC emissions estimated using the PAS2050-1 methodology are usually considered at the national level (Poore and Nemecek, 2018), as prevailing methods to estimate GHG emissions from LUC involve the use of national statistics (Blonk Consultants, 2017). Third, to put the importance of the LUC emissions into perspective with the overall GHG footprint of crops, the LUC emissions of crops estimated at different spatial scales in this study were compared with the cradle-to-farm gate GHG footprints for the same crops (including emissions from fertilizer, energy, etc.) reported in the literature (Clune et al., 2017). This is relevant as most GHG footprinting studies at present (there are a few exceptions e.g. related to oil crops (Schmidt, 2015)), do not include land use change emissions at all (Clune et al., 2017).

The spatial approach outlined above is further elaborated in the materials and methods section, while outcomes of its application to the specified crop dataset and the relevance for crop GHG footprinting are examined in the results and discussion section. Key insights are summarized in the conclusion section.

2. Materials and methods

2.1. LUC emissions of crops

The GHG emissions associated with LUC for a crop c produced at farm i (expressed as kg CO_2 eq t^{-1} crop) ($FP_{LUC,\ c,\ i}$), were calculated using the following equation:

$$FP_{LUC,c,i} = \frac{GHG_{LUC,i}}{Y_{c,i}} * 1000 \tag{1}$$

where

$GHG_{LUC,\ i}$ = Annualized LUC emissions (in t CO_2 eq ha^{-1} yr^{-1}) at farm i

$Y_{c,\ i}$ = Yield of crop c at farm i (in t crop ha^{-1} yr^{-1})

The total annual emissions attributable to LUC at farm i ($GHG_{LUC,\ i}$) were made up of the sum of annualized initial LUC emissions (in t CO_2 eq ha^{-1} yr^{-1}) and the ongoing annual GHG emissions (in t CO_2 eq ha^{-1} yr^{-1}) where cultivation takes place on peat. Initial LUC emissions for cropland conversion from natural land cover included GHG emissions due to i) above- and belowground biomass carbon stock changes, ii) degradation in tropical forest carbon stock due to 'edge effects' induced by LUC in adjacent forest pixels (Chaplin-Kramer et al., 2015) and iii) soil organic carbon (SOC) stock changes in mineral soils. An amortization period of 20 years was used to annualize initial LUC emissions of conversion to cropland, following the PAS2050-1 methodology (BSI, 2012). If cropland was present at a location for 20 years or longer, initial LUC emissions were no longer attributable. The only LUC emissions that could be attributed to these locations were the ongoing annual GHG emissions from SOC in peat soils due to peat drainage, where relevant, based on the global peatland map (Xu et al., 2018). See S4 and S5 of SI for the detailed methodology for calculating $GHG_{LUC,\ i}$.

2.2. Crop yields

Crop yields of farms were collected from the Cool Farm Tool (Hillier et al., 2011), reported as fresh weight. A simple threshold was used to remove farms with physically impossible crop yields, i.e. greater than 1000 t ha^{-1}. Only two farms were removed under this criterion. (See S7 of SI for detailed data cleaning criteria and the number of farms removed by each criterion).

2.3. Connecting previous land cover to farm location

Data on the approximate farm location, i.e. nearest village, town, city, etc. and the area of 1885 farms, in 33 countries producing 69 crops were collected for the year 2014 from the Cool Farm Tool. The locations provided were mapped using the Google geolocation API algorithm (Google Maps Platform, 2019), which provides central, northeast and southwest coordinates (purple dots, Fig. 1), and derived a geographical buffer (thick black boundary in Fig. 1) containing the expected crop production location. This was done by extending the town area (blue region in Fig. 1) by a diameter $2r$, where $A = \pi r^2$, assuming that the farm production area A (provided in the CFT dataset) can be approximated by a circle. The extended vicinity was implemented to account for the uncertainty of the approximate geolocation in the Cool Farm Tool. If the extended area (thick black boundary in Fig. 1) contained less cropland in the ESA-CCI land cover map of 2014 (ESA, 2017) than the farm production area reported, that farm was removed from the dataset since the approach underestimated the farm production area. S7 of SI provides detailed data cleaning criteria and the number of farms removed by each criterion. 1885 out of 2139 farms (or 88%) were retained for the analysis in this study after data cleaning.

Within the geographical boundary of each farm retained, the ESA-CCI land cover map of 1994 (ESA, 2017) was used to identify previous natural land cover (See S1 of SI for the classification of cropland and natural land of the ESA land cover classes and S2 for more detailed explanation of the land conversions).

2.4. LUC emissions

2.4.1. Biomass carbon stock

With the principle of utilizing available data sources considered most suitable for each spatial location, Johnson (2019) combined multiple aboveground biomass datasets using a simple decision-tree approach. Suh et al. (2020) applied the decision-tree approach developed by Johnson (2019) and used a combination of data sources for aboveground biomass stock in a globally consistent manner. The data choices made by Suh et al. (2020) were followed for the aboveground biomass modelling in this study, with an adaptation of using average aboveground biomass values for non-tropical forests for each land cover class-carbon zone, instead of directly adopting the spatially explicit biomass values from Santoro (2018). Rainfed and irrigated cropland classes were assigned an aboveground carbon stock value of zero, assuming cropland classes represent annual croplands. For tropical forest classes, the InVEST 3.7.0. Forest Carbon Edge Effect Model (Sharp et al., 2018) was used to obtain spatially explicit tropical forest aboveground carbon stock values at 300 m × 300 m resolution based on surrounding forest configuration, i.e. distance from forest edges (Chaplin-Kramer et al., 2015). This was chosen as it enabled consideration of the degradation of forest edge biomass on converted and nearby grid cells.

Aboveground carbon stock values for other non-tropical forest classes and mosaic classes containing forests were mapped for each land cover class-carbon zone combination using the average values obtained for the same land cover class-carbon zone combinations in the GlobBiomass dataset for global forest biomass (Santoro, 2018). As in Suh et al. (2020), the Santoro dataset was chosen for mapping non-tropical forests as it provides globally consistent carbon stock values of non-tropical forests at the highest spatial resolution. From there, average estimates of carbon stock values for each land cover class-carbon zone were derived. The land cover class-carbon zone combinations were derived from the intersection of the ESA-CCI land cover map (ESA, 2017) and the carbon zones from Ruesch and Gibbs (2008). For all remaining land cover classes, IPCC default Tier 1 aboveground carbon stock values from Ruesch and Gibbs (2008) were used. Belowground biomass stocks were estimated in proportion to aboveground biomass stocks, using the root:shoot ratio from Eggleston et al. (2006). The aboveground and belowground biomass carbon stock densities used for conversion between carbon stock and biomass values were 0.47 t C t^{-1} aboveground biomass and 0.39 t C t^{-1} belowground biomass respectively (Diop et al., 2016). See S3 of SI for the detailed methodology for mapping aboveground and belowground carbon stock values to land cover classes.

2.4.2. Carbon edge effects

Where forest edges were created as a result of nearby conversion of tropical forests to cropland, the carbon stock losses within these tropical forest edge pixels were considered. The total emissions due to forest carbon stock degradation (sum of the above and belowground carbon stock degradation of each 300 m × 300 m forest pixels adjacent to new cropland converted from tropical forests) within each InVEST model grid cell (100 km × 100 km) (Sharp et al., 2018) were attributed equally to each 300 m × 300 m cropland pixel converted from forests within the same InVEST model grid cell (S4 of SI).

2.4.3. Soil organic carbon

LUC emissions due to changes in SOC stock changes are dependent on the type of soil. While global maps of soil organic carbon are available Wieder et al. (2014), they were not used in this analysis as they do not facilitate the calculation of soil carbon stock changes arising from LUC. For peat soils, ongoing emissions from SOC stock changes due to peat

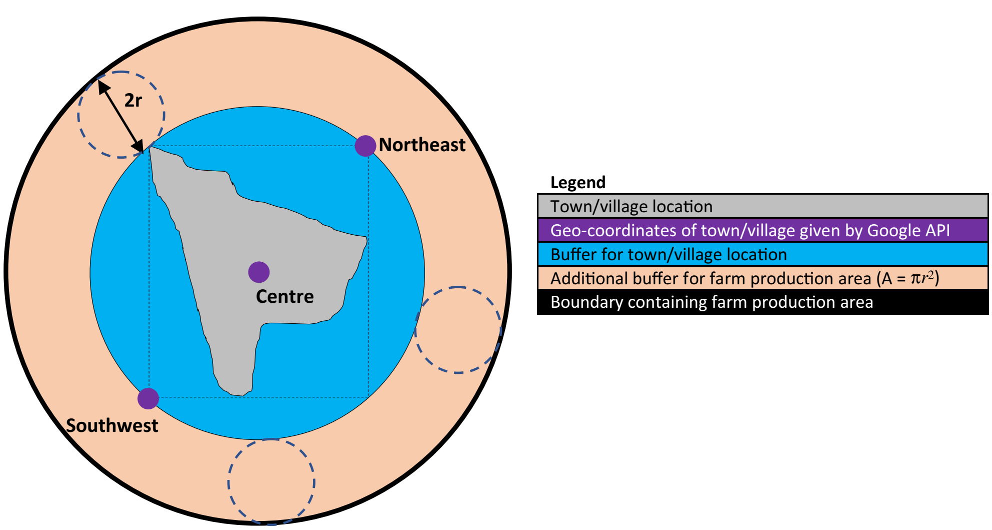


Fig. 1. Geographical boundary used to determine land use change for crop c at farm i.

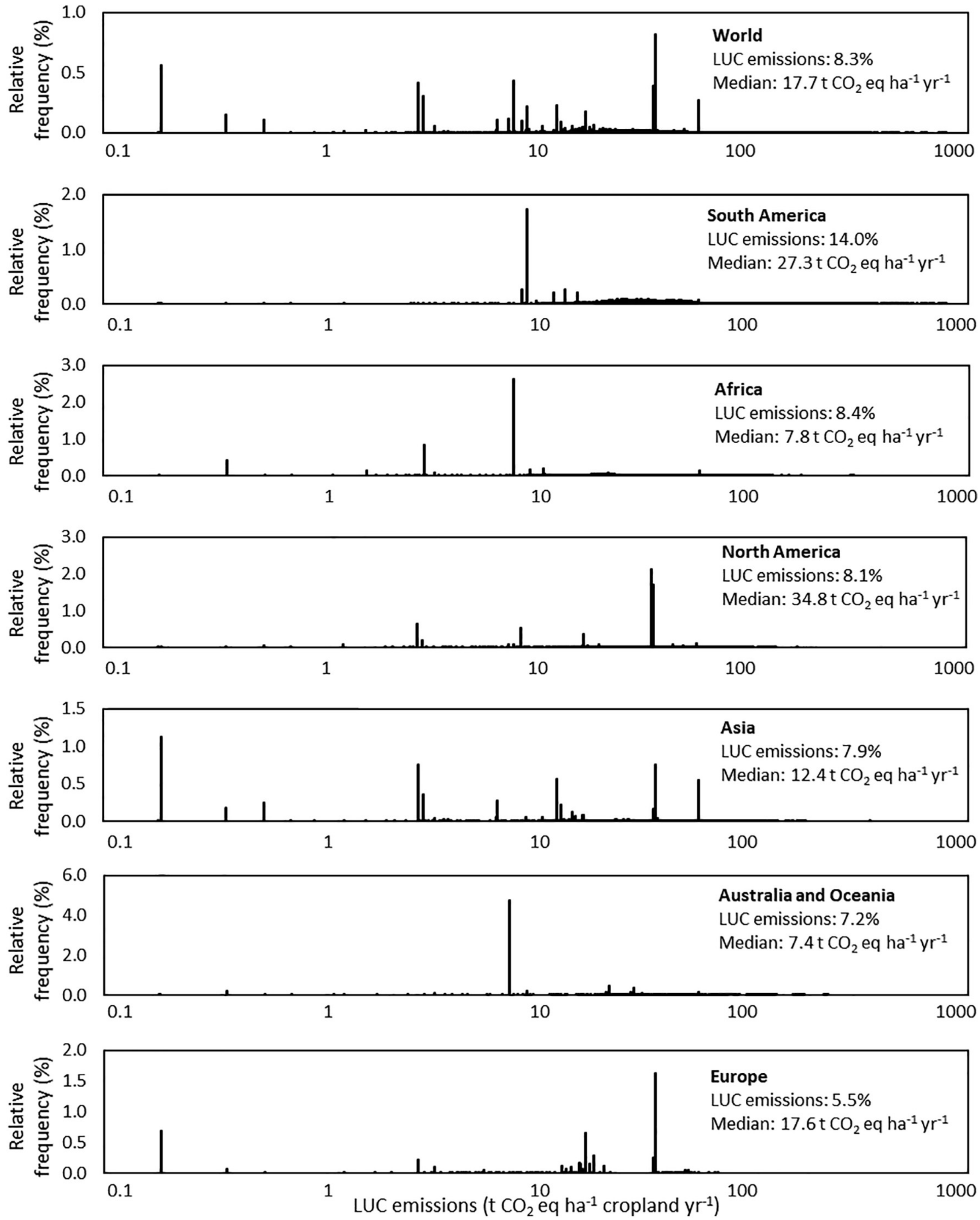


Fig. 2. Relative frequency distribution of LUC emissions due to crop production in 2014 at 300 m × 300 m resolution globally and for each continent. The percentage of pixels with LUC emissions as well as the median of these LUC emissions globally and for each continent are indicated.

drainage for all croplands on peat were estimated at 34.8, 35.5 and 56.6 t CO_2 eq ha^{-1} yr^{-1} in the boreal, temperate and tropical and subtropical regions, respectively (Hiraishi et al., 2014; Ruesch and Gibbs, 2008). As there was not sufficient information regarding any initial LUC emissions generated from peat burning for land clearance globally, peat burning was omitted in the current analysis. For mineral soils, SOC losses were calculated for the top soil layer, i.e. 0–20 cm depth at 3.9 and 2.3 t CO_2 eq ha^{-1} yr^{-1} for land conversion to cropland from forest and grassland, respectively (Deng et al., 2016). All croplands covered by the peat soil map compiled by Xu et al. (2018) were considered to be located on peat soils; all other croplands were located on mineral soils (S4 of SI).

2.5. Comparison between scales and approaches

To compare the LUC emissions of crops calculated at the local scale *l*, (i.e. village/town level) with those calculated at lower spatial resolution, the analysis was repeated using the geographical boundaries at the district *d*, province *p*, and country *z* levels. The geographical boundaries at the district, province and country scale were obtained by locating each geocoded farm (Fig. 1) within the administrative boundary (available from the DIVA-GIS portal (DIVA-GIS, 2019)) with ID2 (district), ID1 (province) and ID0 (country) denotations (Fig. S6 of SI). The Spearman correlation coefficient was used as a measure of the differences between the LUC emissions estimated at the local scale l ($FP_{LUC,\,c,\,i,\,l}$) and those estimated at the district d ($FP_{LUC,\,c,\,i,\,d}$), province p ($FP_{LUC,\,c,\,i,\,p}$) and country z ($FP_{LUC,\,c,\,i,\,z}$) scales. Furthermore, the Spearman's correlation coefficient between the LUC emissions estimated at the local scale l and those calculated using the crop-specific accounting approach based on national statistics (FAOSTAT, 2015) following the PAS2050-1 methodology was calculated. In the latter approach, direct LUC is considered to be potentially relevant when the specific crop area in the country and its corresponding total land type area, i.e. area of perennial crop or annual crop in country, reported increases in the considered time period, i.e. 20 years, and if the area occupied by the natural ecosystem has reported decreases during the same time period (Bengoa et al., 2015). Using the crop-specific approach of allocation, agricultural LUC is allocated to all crops in a given country, according to their respective area increase over the past 20 years. Only the information on the crop type and country of origin (33 countries) of the 1885 farms from the Cool Farm Tool (Hillier et al., 2011) are needed as inputs for estimation of LUC emissions using this approach.

2.6. Comparison with cradle-to-farm-gate GHG footprints of crops from literature

Clune et al. (2017) collated and reviewed 369 studies for the GHG emissions of different fresh food categories. To put the magnitude of the LUC emissions calculated in this study into the perspective of all emissions occurring in crop cultivation, the local scale LUC emission estimates for each crop were compared with the GHG footprints (GHG emissions from cradle-to-farm gate) of the same crops provided by Clune et al. (2017) (See S11 of SI).

3. Results

3.1. LUC emissions of global cropland from ESA land cover in 2014

91.7% of all global cropland pixels were transformed from natural land more than 20 years ago and were not located on peat soils. The remaining 8.3% of global croplands were associated with LUC emissions – either being more recently transformed or being located on peat lands with ongoing emissions. Fig. 2 shows the relative frequency distribution of the cropland pixels with LUC emissions, globally and for each continent. Cropland locations with LUC emissions were mainly located in the Asian continent (37%), South America (20%) and Africa (16%). For cropland locations with LUC emissions, the median LUC emissions by continent were lowest in Australia and Oceania (7.4 t CO_2 eq ha^{-1} cropland yr^{-1}) and highest in North America (34.8 t CO_2 eq ha^{-1} cropland yr^{-1}). See S9 of SI for the LUC emissions due to crop production in 2014 at 300 m $\times$ 300 m resolution globally and for each continent.

3.2. LUC emissions of crops estimated at different spatial scales and using different approaches

Of the 1885 farms, 33% (619 farms) were identified to have LUC emissions when estimated at the local scale. Analysis at coarser spatial scales typically overestimated the LUC emissions of crops. The percentage of farms with LUC emissions increased at coarser spatial scales of analysis, i.e. 87.7%, 99.8% and 100% at the district, province and country scale respectively (Fig. 3). The Spearman's correlation coefficients between the LUC emissions estimated at the local scale and those estimated at the district, province and country scale using the spatial approach, were 0.49, 0.21 and 0.03 respectively.

Comparing the LUC emissions estimated at the local scale to those estimated using the crop-specific national statistics approach gave a Spearman's correlation coefficient of 0.03. See S9 and S10 of SI for related scatter plots.

3.3. Contributors to magnitude of LUC emissions of crops

For the farms in this study with LUC emissions estimated at the local scale, aboveground and belowground carbon stock changes were generally the most important contributors to the magnitude of LUC emissions of crops (Fig. 4). Mineral SOC stock changes had a median contribution of 22% to the LUC emissions of crops. Peat drainage was important, i.e. for at least a quarter of farms with estimated LUC emissions, peat drainage contributed more than 50%. For the locations assessed, very few farms were located adjacent to tropical forest land and therefore, in this case, the contribution of tropical forest edge carbon degradation to the magnitude of LUC emissions was very low. Analysis at coarser spatial scales, could change the relative contribution of these different components of the LUC emissions considerably. For example, for the crops and locations assessed, the contribution of peat drainage to the LUC emissions became more important at the province and country scales of analysis in comparison to the local and district scale estimates, i.e. the median contribution increased from 0% at local and district scales to 30% and 60% at the province and country scales respectively.

3.4. Context with cradle-to-farm gate GHG footprints of crops

Cradle-to-farm gate footprints were available in Clune et al. (2017) for 19 of the crops in the current study. For these crops, this enabled evaluation of the magnitude of local scale LUC emissions determined here, against all emissions occurring in crop cultivation as determined in Clune et al. (2017). For 15 of these 19 crops, the LUC emissions (local scale) were always lower than the contribution of other GHG sources, such as fossil energy and fertilizer use (Fig. 5). However, LUC emissions appeared to be relevant for some farms in the dataset used in this study, i.e. strawberry farms in Poland, raspberry farms in the United States and Poland, soybean farms in Indonesia and wheat farms in Germany. The locations provided for the farms in Poland and the United States were associated with peat drainage; while those in Indonesia and Germany were on lands with previously high above- and belowground carbon stocks.

4. Discussion

This study demonstrates a consistent, globally applicable, spatial approach to estimating LUC emissions associated with crop production. The lack of correlation between the LUC emissions estimated at different scales in this study implies that results estimated at coarser spatial resolution, i.e. district, province and country level, should preferably not be used to approximate LUC emissions of farms. These findings provide evidence that LUC emissions based on national statistics should preferably be updated with local-scale LUC information. Note, however, that exact geo-coordinates of many farms are still unavailable. Information on the exact location of farms would further improve the reliability of the calculations. However, access to these data is often limited. With continued improvements in supply chain traceability and transparency, enabled by technologies such as blockchain (Kamilaris et al., 2019; Oberhauser, 2019), improved specificity of location information is anticipated.

Through the spatially explicit assessment of LUC emissions of crop production, LUC hotspots and associated GHG emissions within a country or supply chain can be identified. Peat emissions were shown to be highly relevant in the LUC emission estimates of some crops, particularly for strawberry farms in Poland and raspberry farms in United States and Poland. Poland and United States, together with Finland, Ireland, Sweden, Canada, United Kingdom, Indonesia and Malaysia, have one of the most peat lands per land area worldwide (Montanarella et al., 2006; Xu et al., 2018). Cultivation of crops in

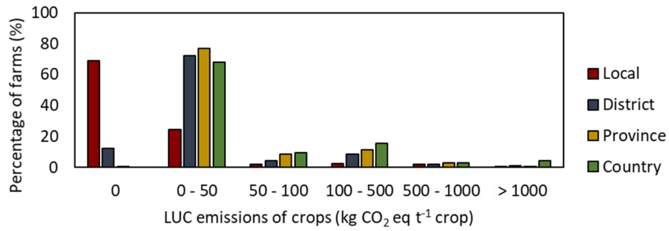


Fig. 3. Histogram of LUC emissions of crops of the 1885 farms, calculated at different spatial scales.

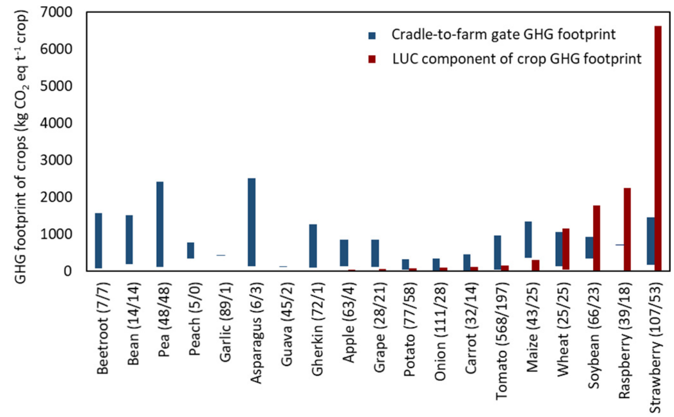


Fig. 5. The range (Minimum to maximum) of cradle-to-farm gate GHG footprint of crops from Clune et al. (2017), in most cases excluding LUC emissions, compared to the range (minimum to maximum) of LUC emissions (local scale) of the same crops in this study. The crops are arranged according to increasing maximum LUC emissions. The first number in the parenthesis represents the total number of observations of each crop in the dataset used in this study; the second number represents how many of those have LUC emissions.

these countries may hence be associated with emissions from peat drainage, even if those crops are not commonly known to be cultivated on peat lands, as in the case for oil palm in Indonesia, for example (Liedke et al., 2017). As peat emissions are not routinely considered in LUC emissions accounting, the results of this study point towards the importance of considering this emission type.

Emissions from above- and belowground carbon stock changes were generally the most important contributors to the magnitude of LUC emissions of crops for the dataset in this study. These emissions were particularly high for soybean farms in Indonesia and wheat farms in Germany. This can be explained by the fact that the aboveground carbon stock densities for non-tropical forests and mosaic classes pre-existing cropland in Indonesia and Germany were, on average, 226 t C ha^{-1} and 162 t C ha^{-1} respectively, both larger than the global average aboveground carbon stock density of non-tropical forests and mosaic classes, calculated as 108 t C ha^{-1} (Santoro, 2018). Although emissions due to forest edge carbon degradation in the tropics were negligible for farms in this study, Lam et al. (2019) showed that carbon edge effects contributed between 1% and 52% of the GHG footprints of crude palm oil production in different parts of Indonesia. Note that forest edge effects in temperate and boreal regions were not considered, as there is currently no available empirical research to support consistent estimation of forest carbon stocks with respect to surrounding forest configuration in these regions (Reinmann and Hutyra, 2017).It was also found that LUC emissions cannot be considered negligible compared to other GHG emission sources, i.e. fertilizer application and energy use, especially in high carbon stock regions or those with a high concentration of peat land. This is consistent with past studies, which showed that LUC emissions can dominate product GHG footprints, e.g. rubber in Thailand (Jawjit et al., 2010), oil palm in Indonesia (Lam et al., 2019), soybean in Argentina and Brazil (Flynn et al., 2012).

The demonstrated approach could be further refined, as the land cover map from ESA (2017) is limited by the lack of differentiation between i) specific crop types (e.g. corn, wheat), ii) perennial (e.g. plantations) and annual croplands, and iii) different land covers within the mosaic cropland pixels (See S1 of SI). Moreover, all areas classified as cropland were assumed to represent annual croplands, so that temporary carbon sequestration was not taken into account due to regular harvest of the annual crops compared to perennial crops. The LUC emissions calculated here could be corrected for any known carbon sequestration effects of specific crops. Furthermore, future studies may consider GHG emissions arising from indirect LUC as the methods for their quantification become more refined (Kløverpris and Mueller, 2013; Schmidt et al., 2015), although Daioglou et al. (2020) question the effectiveness of indirect LUC accounting in determining the GHG performance of crop production, as well as its usefulness as a guiding principle for land-use and climate policy. In regard to future methodological development, it is clear that earth observation data are continuing to improve at pace in terms of spatial resolution, precision of land cover classification and other EO-derived vegetation indices (Ramirez-Reyes et al., 2019); these may be better indicators of biomass production than LULC-based proxies. Together with the improvements in supply chain traceability, these advances may provide opportunities for further improvements in impact assessment to inform land management and regenerative practices and policies, such as establishment and maintenance of riparian strips and forest and woodland areas with improved connectivity.

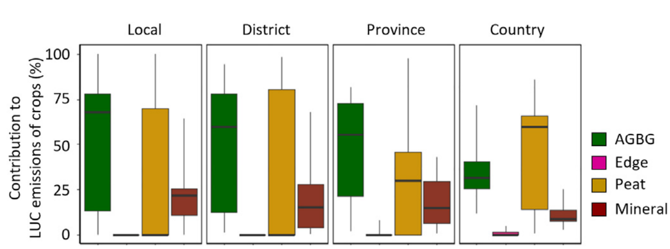


Fig. 4. Contribution to the magnitude of LUC emissions of crops for farms with LUC emissions, by component: aboveground and belowground carbon stock changes (AGBG), forest edge carbon degradation (Edge), peat drainage (Peat) and mineral SOC stock changes (Mineral). The number of farms with LUC emissions is 619, 1654, 1881 and 1885 at the local, district, province and country scale of analysis respectively. The variability diagrams show the 5th percentile, first quartile, median, third quartile, and 95th percentile. Percentage contribution outside of this range are not presented.

Beyond LUC emissions accounting, the spatial approach of using boundaries to represent approximate farm locations can be used to enhance broader consideration of geographical variability in impact assessment, supporting more accurate, regionalized impact assessments of agricultural production (Bulle et al., 2019; Mutel et al., 2019). The development of spatial approaches can improve both the modelling and understanding of environmental impacts and in turn provide insights to inform more sustainable practices in agriculture and landscape management.

5. Conclusion

Consideration of LUC emissions is important for GHG accounting of crop production, not just for those crops commonly associated with cultivation in high carbon stock regions. Moreover, analysis at a high spatial resolution is needed to reflect the spatial variability of GHG footprints induced by LUC. The spatial representation of GHG footprints can enable buyers to purchase from production associated with lowest impacts, and the methodological approaches can be adapted for scenario assessments to help select land development options resulting in lowest LUC emissions. Further refinements to the assessment of

GHG emissions from LUC should be conducted as supply chain traceability improves.

CRediT authorship contribution statement

W.Y.L., J.C., S.S. and M.A.J.H. developed the research; W.Y.L. and J.C. performed the calculations and spatial analyses; and all contributed to the writing of the paper.

Funding sources

The study is part of the RELIability of product Environmental Footprints (RELIEF) project, which is funded by the Europeans Union's Horizon 2020 research and innovation program under the Marie Sklodowska-Curie grant agreement No. 641459.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors would like to thank Tom Moxon, Giles Rigarlsford, Lau Tambjerg and Henry King from Unilever for their technical support and feedback on the drafts. We would also like to acknowledge the ESA CCI Land Cover project for the use of the CCI-LC products in our research; as well as the processed maps from sources including the ESA CCI Land Cover project, InVEST suite of The Natural Capital Project, PEATMAP project and the Ruesch and Gibbs paper as part of our abstract art.

Appendix A. Supplementary data

ESA land cover classification. Land cover change attributable to cropland expansion. Mapping aboveground and belowground carbon stock values to land cover classes. LUC emissions of each cropland pixel. LUC emissions of farms. LUC emissions of farms with less specific location information. Data cleaning. Results of LUC emissions of pixels. Results of LUC emissions of crops at different spatial scales. Results of comparison with crop-specific national statistics approach. Results of comparison with cradle-to-farm gate GHG footprint. Supplementary data to this article can be found online at doi:https://doi.org/10.1016/j.scitotenv.2020.143338.

References

Avitabile, V., Herold, M., Heuvelink, G.B., Lewis, S.L., Phillips, O.L., Asner, G.P., Armston, J., Ashton, P.S., Banin, L., Bayol, N., 2016. An integrated pan-tropical biomass map using multiple reference datasets. Glob. Chang. Biol. 22, 1406–1420.

Baccini, A., Goetz, S., Walker, W., Laporte, N., Sun, M., Sulla-Menashe, D., Hackler, J., Beck, P., Dubayah, R., Friedl, M., 2012. Estimated carbon dioxide emissions from tropical deforestation improved by carbon-density maps. Nat. Clim. Chang. 2, 182.

Bengoa, X., Rossi, V., Humbert, S., Nemecek, T., Lansche, J., Mouron, P., Riedener, E., 2015. Methodological Guidelines for the Life Cycle Inventory of Agricultural Products. Version 3.0, July 2015. World Food LCA Database (WFLDB). Quantis and Agroscope, Lausanne and Zurich, Switzerland.

Blonk Consultants, 2017. Direct Land Use Change Assessment Tool, Version 2017.2. Blonk Consultants, Gouda (2017).

BSI, 2012. PAS 2050–1: 2012 Assessment of Life Cycle Greenhouse Gas Emissions from Horticultural Products. Supplementary Requirements for the Cradle to Gate Stages of GHG Assessments of Horticultural Products Undertaken in Accordance with PAS 2050. British Standards Institution, London.

Bulle, C., Margni, M., Patouillard, L., Boulay, A.-M., Bourgault, G., De Bruille, V., Cao, V., Hauschild, M., Henderson, A., Humbert, S., Kashef-Haghighi, S., Kounina, A., Laurent, A., Levasseur, A., Liard, G., Rosenbaum, R.K., Roy, P.-O., Shaked, S., Fantke, P., Jolliet, O., 2019. IMPACT world+: a globally regionalized life cycle impact assessment method. Int. J. Life Cycle Assess. 24, 1653–1674.

Chaplin-Kramer, R., Ramler, I., Sharp, R., Haddad, N.M., Gerber, J.S., West, P.C., Mandle, L., Engstrom, P., Baccini, A., Sim, S., 2015. Degradation in carbon stocks near tropical forest edges. Nat. Commun. 6, 10158.

Clune, S., Crossin, E., Verghese, K., 2017. Systematic review of greenhouse gas emissions for different fresh food categories. J. Clean. Prod. 140, 766–783.

Daioglou, V., Woltjer, G., Strengers, B., Elbersen, B., Barberena Ibañez, G., Sánchez Gonzalez, D., Gil Barno, J., van Vuuren, D.P., 2020. Progress and barriers in understanding and preventing indirect land-use change. Biofuels Bioprod. Biorefin. 14 (5), 924–934.

Davis, S.J., Burney, J.A., Pongratz, J., Caldeira, K., 2014. Methods for attributing land-use emissions to products. Carbon Management 5, 233–245.

Deng, L., Zhu, G.-y., Tang, Z.-s., Shangguan, Z.-p., 2016. Global patterns of the effects of land-use changes on soil carbon stocks. Global Ecology and Conservation 5, 127–138.

Diop, S., Scheren, P., Machiwa, J.F., 2016. Estuaries: A Lifeline of Ecosystem Services in the Western Indian Ocean. Springer.

DIVA-GIS, 2019. World administrative boundaries. http://www.diva-gis.org/gdata.

Eggleston, S., Buendia, L., Miwa, K., Ngara, T., Tanabe, K., 2006. 2006 IPCC guidelines for national greenhouse gas inventories. Volume 4: Agriculture, Forestry and Other Land Use. Intergovernmental Panel on Climate Change.

ESA, 2017. Land cover maps - v2.0.7. Product user guide version 2.0. available at. http://maps.elie.ucl.ac.be/CCI/viewer/download/ESACCI-LC-Ph2-PUGv2_2.0.pdf.

FAOSTAT (2015) Food and agriculture Organization of the United Nations Statistics Division. Retrieved from: http://faostat3.fao.org/home/E on 12 February 2016.

Flynn, H.C., Canals, L.M.i., Keller, E., King, H., Sim, S., Hastings, A., Wang, S., Smith, P., 2012. Quantifying global greenhouse gas emissions from land-use change for crop production. Glob. Chang. Biol. 18, 1622–1635.

Google Maps Platform, 2019. Google geocoding API. https://developers.google.com/maps/documentation/geocoding/.

Hillier, J., Walter, C., Malin, D., Garcia-Suarez, T., Mila-i-Canals, L., Smith, P., 2011. A farm-focused calculator for emissions from crop and livestock production. Environ. Model Softw. 26, 1070–1078.

Hiraishi, T., Krug, T., Tanabe, K., Srivastava, N., Baasansuren, J., Fukuda, M., Troxler, T., 2014. 2013 Supplement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories: Wetlands. IPCC, Switzerland.

Houghton, R.A., House, J.I., Pongratz, J., van der Werf, G.R., DeFries, R.S., Hansen, M.C., Le Quéré, C., Ramankutty, N., 2012. Carbon emissions from land use and land-cover change. Biogeosciences 9, 5125–5142.

IPCC (2019) Climate Change and Land: An IPCC Special Report on Climate Change, Desertification, Land Degradation, Sustainable Land Management, Food Security, and Greenhouse Gas Fluxes in Terrestrial Ecosystems. [P.R. Shukla, J. Skea, E. Calvo Buendia, V. Masson-Delmotte, H.-O. Pörtner, D. C. Roberts, P. Zhai, R. Slade, S. Connors, R. van Diemen, M. Ferrat, E. Haughey, S. Luz, S. Neogi, M. Pathak, J. Petzold, J. Portugal Pereira, P. Vyas, E. Huntley, K. Kissick, M. Belkacemi, J. Malley, (eds.)]. (In press).

Jawjit, W., Kroeze, C., Rattanapan, S., 2010. Greenhouse gas emissions from rubber industry in Thailand. J. Clean. Prod. 18, 403–411.

Johnson, J., 2019. Globally Harmonized Carbon Storage Data Using a Simple Decision Tree Approach.

Kamilaris, A., Fonts, A., Prenafeta-Boldύ, F.X., 2019. The rise of blockchain technology in agriculture and food supply chains. Trends Food Sci. Technol. 91, 640–652.

Kløverpris, J.H., Mueller, S., 2013. Baseline time accounting: considering global land use dynamics when estimating the climate impact of indirect land use change caused by biofuels. Int. J. Life Cycle Assess. 18, 319–330.

Kulak, M., Sim, S., King, H., Lam, W.Y., Marquardt, S., Huijbregts, M., 2018. Tracking current and forecasting future land-use impacts of agricultural value chains. 67th discussion forum on life cycle assessment, 3rd of November 2017, Zurich, Switzerland. Int. J. Life Cycle Assess. 23, 1520–1524.

Lam, W.Y., Kulak, M., Sim, S., King, H., Huijbregts, M.A.J., Chaplin-Kramer, R., 2019. Greenhouse gas footprints of palm oil production in Indonesia over space and time. Sci. Total Environ. 688, 827–837.

Lambin, E.F., Gibbs, H.K., Heilmayr, R., Carlson, K.M., Fleck, L.C., Garrett, R.D., le Polain de Waroux, Y., McDermott, C.L., McLaughlin, D., Newton, P., Nolte, C., Pacheco, P., Rausch, L.L., Streck, C., Thorlakson, T., Walker, N.F., 2018. The role of supply-chain initiatives in reducing deforestation. Nat. Clim. Chang. 8, 109–116.

Liedke, A., Eggers, D., Gruenenwald, T., Mckeown, P., Schneider, C., Schowanek, D., Gonzalez, M., Lehmann, A., 2017. Calculation of Greenhouse Gas (GHG) emissions caused by direct land use change and cultivation on peat soil for palm kernel oil-based precursors of surfactants. Report for the ERASM Surfactant Life Cycle and Ecofootprinting (SLE) Project, July 2017. http://www.erasm.org.

Montanarella, L., Jones, R.J., Hiederer, R., 2006. The Distribution of Peatland in Europe.

Mutel, C., Liao, X., Patouillard, L., Bare, J., Fantke, P., Frischknecht, R., Hauschild, M., Jolliet, O., Maia de Souza, D., Laurent, A., Pfister, S., Verones, F., 2019. Overview and recommendations for regionalized life cycle impact assessment. Int. J. Life Cycle Assess. 24, 856–865.

Oberhauser, D., 2019. Blockchain for environmental governance: can smart contracts reinforce payments for ecosystem services in Namibia? Frontiers in Blockchain 2.

Peter, C., Helming, K., Nendel, C., 2017. Do greenhouse gas emission calculations from energy crop cultivation reflect actual agricultural management practices? – a review of carbon footprint calculators. Renew. Sust. Energ. Rev. 67, 461–476.

Poore, J., Nemecek, T., 2018. Reducing food's environmental impacts through producers and consumers. Science 360, 987–992.

Powers, J.S., Corre, M.D., Twine, T.E., Veldkamp, E., 2011. Geographic bias of field observations of soil carbon stocks with tropical land-use changes precludes spatial extrapolation. Proc. Natl. Acad. Sci. 108, 6318–6322.

Ramirez-Reyes, C., Brauman, K.A., Chaplin-Kramer, R., Galford, G.L., Adamo, S.B., Anderson, C.B., Anderson, C., Allington, G.R.H., Bagstad, K.J., Coe, M.T., Cord, A.F., Dee, L.E., Gould, R.K., Jain, M., Kowal, V.A., Muller-Karger, F.E., Norriss, J., Potapov, P., Qiu, J., Rieb, J.T., Robinson, B.E., Samberg, L.H., Singh, N., Szeto, S.H., Voigt, B.,

Watson, K., Wright, T.M., 2019. Reimagining the potential of Earth observations for ecosystem service assessments. Sci. Total Environ. 665, 1053–1063.
Reinmann, A.B., Hutyra, L.R., 2017. Edge effects enhance carbon uptake and its vulnerability to climate change in temperate broadleaf forests. Proc. Natl. Acad. Sci. 114, 107–112.
Ruesch, A., Gibbs, H.K., 2008. New IPCC Tier-1 Global Biomass Carbon Map for the Year 2000.
Saatchi, S.S., Harris, N.L., Brown, S., Lefsky, M., Mitchard, E.T., Salas, W., Zutta, B.R., Buermann, W., Lewis, S.L., Hagen, S., 2011. Benchmark map of forest carbon stocks in tropical regions across three continents. Proc. Natl. Acad. Sci. 108, 9899–9904.
Santoro, M., 2018. GlobBiomass - Global Datasets of Forest Biomass. PANGAEA.
Schmidt, J.H., 2015. Life cycle assessment of five vegetable oils. J. Clean. Prod. 87, 130–138.
Schmidt, J.H., Weidema, B.P., Brandão, M., 2015. A framework for modelling indirect land use changes in Life Cycle Assessment. J. Clean. Prod. 99, 230–238.
Sharp, R., Tallis, H., Ricketts, T., Guerry, A., Wood, S., Chaplin-Kramer, R., Nelson, E., Ennaanay, D., Wolny, S., Olwero, N., 2018. InVEST 3.7.0. User's Guide. The Natural Capital Project. Stanford University, University of Minnesota, The Nature Conservancy, and World Wildlife Fund.
Smith, G.P.,.D., Vis, J.K., Studley, S., King, V., 2015. Sustainable Agriculture Code. https://www.unilever.com/.Images/sac-2015_tcm244-427050_en.pdf. (Accessed 19 June 2016).
Smith, W., Nelson, E., Johnson, J., Polasky, S.C., Milder, J., S. Gerber, J., West, P., Siebert, S., Brauman, K., Carlson, K., Arbuthnot, M.P., Rozza, J., Pennington, D., 2019. Voluntary Sustainability Standards Could Significantly Reduce Detrimental Impacts of Global Agriculture.
Suh, S., Johnson, J.A., Tambjerg, L., Sim, S., Broeckx-Smith, S., Reyes, W., Chaplin-Kramer, R., 2020. Closing yield gap is crucial to avoid potential surge in global carbon emissions. Glob. Environ. Chang. 63, 102100.
Unilever, 2018. 2017 Palm Oil Mills. Retrieved from. https://www.unilever.com/Images/unilever-palm-oil-mill-list_tcm244-515895_en.pdf on 8 May 2019.
van Beijma, S., Chatterton, J., Page, S., Rawlings, C., Tiffin, R., King, H., 2018. The challenges of using satellite data sets to assess historical land use change and associated greenhouse gas emissions: a case study of three Indonesian provinces. Carbon Management 9, 399–413.
Wang, S., Wang, W., Yang, H., 2018. Comparison of product carbon footprint protocols: case study on medium-density fiberboard in China. Int. J. Environ. Res. Public Health 15, 2060.
Wieder, W.R., Boehnert, J., Bonan, G.B., Langseth, M., 2014. Regridded harmonized world soil database v1.2. Data set. Retrieved from. http://daac.ornl.gov.
Xu, J., Morris, P., Liu, J., Holden, J., 2018. PEATMAP: refining estimates of global peatland distribution based on a meta-analysis. Catena 160, 134–140.